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RESEARCH ARTICLE

ScenicPlanner: planning scenic travel routes leveraging heterogeneous user-generated digital footprints

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Abstract To facilitate the travel preparation process to a city, a lot of work has been done to recommend a POI or a sequence of POIs automatically to satisfy users' needs. However, most of the existing work ignores the issue of planning the detailed travel routes between POIs, leaving the task to online map services or commercial GPS navigators. Such a service or navigator in terms of suggesting the shortest travel distance or time, which cannot meet the diverse requirements of users. For instance, in the case of traveling by driving for leisure purpose, the scenic view along the travel routes would be of great importance to users, and a good planning service should put the sceneries of the route in higher priority rather than the distance or time taken. To this end, in this paper, we propose a novel framework called *ScenicPlanner* for route recommendation, leveraging a combination of geotagged image and check-in digital footprints from location-based social networks (LBSNs). First, we enrich the road network and assign a proper scenic view score to each road segment to model the scenic road network, by extracting relevant information from geo-tagged images and check-ins. Then, we apply heuristic algorithms to *iteratively* add road segment and determine the travelling order of added road segments with the objective of maximizing the total scenic view score while satisfying the user-specified constraints (i.e., origin, destination and the total travel distance). Finally, to validate the efficiency and effectiveness of the proposed framework, we conduct extensive experiments on three real-world data sets from the Bay Area in the city of San Francisco, which contain a road network crawled from OpenStreetMap, more than 31 000 geo-tagged images generated by 1 571 Flickr users in one year, and 110 214 check-ins left by 15 680 Foursquare users in six months.

Keywords scenic view, travel route planning, heterogeneous, digital footprint

1 Introduction

Planning an itinerary before travelling to a city is one of the most important travel preparation activities [1]. To figure out a route with the best sightseeing experience, a user may not only have to browse as many profiles of Point of Interests (POIs) as possible to pick up his/her preferred one(s), but also need to determine the order of travelling, which is very time-consuming and labor-intensive [2–4]. To facilitate the trip planning process, a number of online trip planners (e.g., NileGuide[1)], YourTour[2)]) rank the city landmarks to guide users to select interesting places to visit, and also help users to organize the travel order of the selected POIs. Moreover, with

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1) https://www.nileguide.com/
2) http://www.yourtour.com/

the increasing popularity of location-based social networks (LBSNs), various digital footprints recording the interactions between human and cyber-physical worlds are accumulated at an unprecedented scale [5–7]. Rich and valuable information regarding the POIs and users, such as the POI's physical coordinate, category, popularity and the check-in preference are contained *explicitly* or *implicitly* in such digital footprints [8, 9]. Such data can be mined for automatic trip planning under different user scenarios [10, 11]. However, most current trip planning systems recommend either a single POI or a sequence of POIs, neglecting the detailed travel route planning issue between two suggested consecutive POIs. Although available on-line map services such as Google Maps[3] and Baidu Maps[4] or commercial GPS navigators can be easily integrated, the suggested travel routes just cannot meet diverse user requirements since they usually provide routes with the shortest travel distance or time. In real life, particularly in the case of travelling for leisure purpose by driving a car [12, 13], users probably are not rushing in reaching the next destination, but the visual and scenic attributes along the driving routes are more preferred instead [12]. *Thus, beyond the shortest distance (or time), in the paper, we aim to recommend the travel route between two POIs with the best scenic view.*

Intuitively, to plan a scenic travel route from one POI to another, we can design one that passes by a few famous tourist attractions (or landmarks) under user constraints. However, the solution is problematic and invalid due to the following two reasons. Fist of all, the activity of sightseeing during driving has a distinct nature from the activity of visiting tourist attractions. Specifically, users would still get a beautiful scene view along the travel routes even if there is no tourist attraction passing by (e.g., "The Embarcadero" at San Francisco), while paying visits to tourist attraction, users have to make a dedicated stay for a certain duration to visit a number of *indoor tourist attractions* (e.g., stay several hours at "The Louvre" museum to visit the famous artworks). Second, some landmarks may be far away from the road and *invisible* when users are in car, thus cannot offer a pleasant driving experience. In essence, it is the overall scenic environment along the roads that contributes the beautifulness. The problem of the scenic travel route planning can be divided into two subproblems, modelling scenic road network, and finding the route with the maximum scenic score under the given constraints. To ensure the feasibility of our method, we need to address the following two research challenges.

- How to model the scenic road network? The goal of the scenic road network modelling is to score each road segment in the road network correctly, according to its nearby "scenic environment". Nevertheless, the term is rather subjective which depends on its popularity, user's preference, the visiting time and so on, making the modelling task quite challenging.
- How to find the quasi-optimal route efficiently? Being able to score each road segment, from a starting point to an ending point, the problem becomes the well-known path-finding problem, which is proved to be NP-hard. To get a high-quality solution, we have to determine that how many road segments to be travelled, and the travelling order as well, suffering from the combination complexity in nature. What is worse, for a targeted travelling road segment, it usually has two driving directions which complicates the problem further.

With the above-mentioned research objective and challenges, the main contributions of the paper are:

- We propose a novel framework called *ScenicPlanner*, which contains two functional modules (i.e., the scenic road network modelling and the scenic route planning) to plan a travel route between two given points, with the objective of maximizing the scenic view score to gain the most excellent driving experience.
- On the basis of the road network crawled from the crowdsourcing platform (i.e., OpenStreetMap (OSM)[5]), we enrich it and assign a scenic view score to each road segment in a comprehensive way, leveraging the complementary information provided by a combination of geo-tagged images and check-ins from two LBSNs platforms (i.e., Flickr[6] and Foursquare[7]).
- We propose a heuristic algorithm to find the near-optimal routes, and validate its effectiveness and efficiency in the city of San Francisco, USA, through extensive experiments based on large-scale real-world data sets, consisting of more than 31 000 geo-tagged images generated by 1 571 Flickr users in a year, and 110 214 check-ins left by 15 680 Foursquare users in six

[3] https://maps.google.com/
[4] https://map.baidu.com/
[5] http://www.openstreetmap.org/
[6] https://www.flickr.com/
[7] https://foursquare.com/

months. As a comparison, we also propose two baseline methods. Results demonstrate that the proposed algorithm can achieve the best performance.

The rest of the paper is organized as follows. In Section 2, after presenting some basic concepts and introducing the problem formulation, we overview the framework of our proposed ScenicPlanner system. We present the process of modelling the scenic road network by leveraging the Flickr geo-tagged images and Foursquare check-ins in Section 3, and elaborate on our scenic route planning approach in Section 4. We evaluate the performance of the proposed framework in Section 5. In Section 6, we review the related work and show how this paper differs from prior research. Finally, we conclude the paper and chart the future directions in Section 7.

2 The overview of ScenicPlanner system

In this section, we provide definitions of some basic concepts, give a formal problem statement of scenic travel route planning, and present a brief description of ScenicPlanner framework, which is comprised of two major parts: a scenic road network model and a scenic route planning component, as shown in Fig. 1.

2.1 Basic concepts

Definition 1 (Road network) A road network is a graph $G(N, E)$, consisting of a node set N and an edge set E, where each element n in N is an intersection with a pair of longitude and latitude coordinates (x, y) representing its spatial location. Edge set E is a subset of the cross product $N \times N$. Each element $e(u, v)$ in E is a road segment connecting node u and node v.

Definition 2 (A travel route) A travel route TR is a sequence of nodes $(n_1, n_2, \ldots, n_i, \ldots, n_k)$, in which between any two consecutive nodes $\langle n_i, n_{i+1}\rangle$, there exists a road segment (i.e., an edge) $e(n_i, n_{i+1})$ in the road network. Alternatively, a travel route can be also defined as a sequence of road segments, in which between any two consecutive road segments they share a unique node.

Definition 3 (A geo-tagged image) A geo-tagged image is defined as a quadruple $gim = (u_{id}, x_i, y_i, t_i)$, showing a user with id u_{id} took an image at location (x_i, y_i) at time t_i using Flickr.

Definition 4 (A check-in) A check-in is defined as a triple $ck = (u_{id}, v_{id}, t_i)$, showing a user with id u_{id} checked-in a venue (i.e., POI) with id v_{id} at time t_i using Foursquare. In addition, Foursquare provides the physical coordinates, tags and the category information about an any given venue.

Definition 5 (Scenic score of a road segment) Given a road segment $e(i, j)$, function $\mathcal{S}(e(i, j)) \rightarrow R^+$ assigns a score to reflect its scenic environment. A higher score, a more beautiful scene it is. A road segment with score greater than 0 is also called scenic road segment.

Definition 6 (Scenic score of a travel route) The scenic score of a travel route TR is defined as the sum of the scenic score of all road segments that the travel route contains, and thus can be computed by $\sum_{i=1}^{k-1} \mathcal{S}(e(n_i, n_{i+1}))$, where k is the number of road segments that TR contains.

Definition 7 (A travel route query) A travel route query (TRQ) consists of three parts: 1) a user-specified starting point $p_o = (x_o, y_o)$; 2) a user-specified ending point $p_d = (x_d, y_d)$; and 3) the maximum travel distance of the targeted

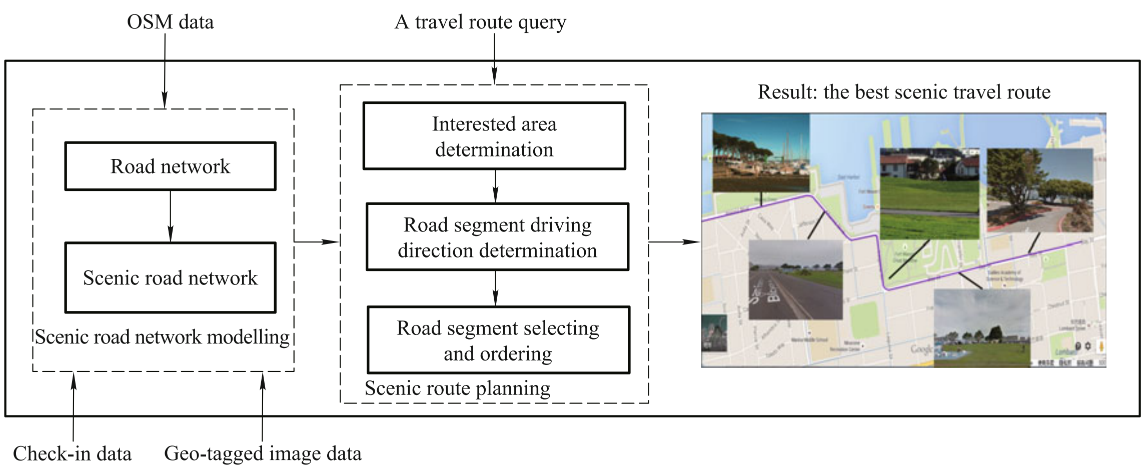


Fig. 1 The framework of our proposed ScenicPlanner

travel route $Dist_{\max}$. In summary, the query TRQ can thus be represented as $(p_o, p_d, dist_{\max})$.

2.2 Problem formulation

The problem of planning scenic travel route can be formulated as follows:

Given:

1) a user's travel route query (TRQ);
2) a collection of geo-images and check-ins from the targeted city;
3) a road network $G(N, E)$ of the targeted city.

Model the scenic road network by designing a proper function $\mathcal{S}(\cdot)$ to score each road segment leveraging the collection of geo-tagged images and check-ins, then find the travel route which maximizes its scenic score while satisfying the user's TRQ.

Theorem 1 The scenic travel route planning problem is NP-hard.

Proof For a set of road segments $\{e(i, j)\}$, each of them has a scenic score $\mathcal{S}(e(i, j))$ reflecting its sightseeing, in analogy to the case that each item has a value in the Knapsack problem [14]. On the other hand, users have to travel a certain distance to visit a scenic road from a given source to a destination, in analogy to the case that each item has a weight. The maximum travel distance imposed by the user is just similar to the maximum weight capacity in the Knapsack problem. More complicatedly, different travelling orders of the same set of scenic roads need different travel distances, and different traversed directions would also result in varied total travel distances, even for a same scenic road. Therefore, the problem discussed in the paper can be viewed as a variant of Knapsack problem, which is NP-hard.

2.3 ScenicPlanner framework

As shown in Fig. 1, the ScenicPlanner is consist of two modulars, *scenic road network modelling* and *scenic route planning* respectively. With the inputs from three data sets, i.e., the road network, the geo-tagged image data and check-ins data, the *scenic road network modelling* modular enriches the road network by extracting relevant information from the geo-tagged image and check-ins data. The *scenic route planning* modular works in a *query-response* manner. To be more specific, after being triggered by a user-inputed travel query, it first determines the interested area according to the locations of starting and ending points, and only road segments lying in the interested area can be qualified to be travelled. As each candidate road segment has two driving directions, we then apply a heuristic rule to determine its driving direction. Finally, road segment selecting and ordering operation finds the travel route with the best scenic view. We elaborate the details of each component in the next two sections.

3 Scenic road network modelling

As discussed adove, the key issue of modelling the scenic road network is to score each road segment (i.e., the degree of beautifulness) according to its landscape quality. Previous studies on quantifying the factors contributing to the scenic beauty of routes concluded that scenic routes usually have a higher density of surrounding geo-tagged photos and some specific landscape features (i.e., a good visibility to POIs with some specific categories, such as the foreground river and garden) [12, 13]. Bringing this idea in and going a step further, we leverage the complementary information provided by geo-tagged image and check-in data to score the scenic view of a given road segment, detailed as follows.

3.1 Geo-tagged images and scenic view score

A high density of geo-tagged images surrounding a road segment is a good indicator of its quality of scenic view. However, a higher value of density may not necessarily lead to a better scenic view. The dominate direction of the distribution is also of great importance. For instance, a better sightseeing from the road might be guaranteed if the dominate direction of the geo-tagged image distribution is consistent with the direction of the road. The rationale behind is: users would probably take photos along the road if they are attracted by its overall view, while users would take photos from different standpoints around a center location if they are attracted by a nearby landmark. Taking the two distributions shown in Fig. 2 as an example, though they have the same density, the road segment in the left case should be scored higher. Thus we consider both the density and dominate direction of the geo-image data distribution collectively, and compute the scenic score of a given road segment as follows:

$$\begin{aligned}\mathcal{S}_{image}(e(n_i, n_j), \{gim\}) = w(e(n_i, n_j), \{gim\}) \times \\ \log[sizeof(\{gim | dist(gim.(x_i, y_i), e(n_i, e_j)) < \delta\})], \quad (1)\end{aligned}$$

where $dist((x_i, y_i), e(n_i, n_j))$ computes the geo-distance from point (x_i, y_i) to the road segment $e(n_i, n_j)$, δ is a user-specified parameter. $sizeof(\cdot)$ gets the number of elements in the set, indicating that only the geo-tagged images with the distance less than δ are counted when calculating the density to ensure the visibility. w is a weighting factor which considers the road direction and the dominate direction of the distribution, and it is calculated by Eq. (2).

$$\{\lambda_1, \lambda_2\} = \mathrm{PCA}(\{gim|dist(gim.(x_i, y_i), e(n_i, e_j)) < \delta\}),$$

$$w(e(n_i, n_j), \{gim\}) = \cos(\alpha) \cdot \lambda_1 + \sin(\alpha) \cdot \lambda_2,$$

$$\alpha = \arccos(\frac{\vec{d_1} \cdot \vec{d_r}}{|\vec{d_1}| \cdot |\vec{d_r}|}), \tag{2}$$

where λ_1 and λ_2 are the eigenvalues corresponding to the first and second principal components ($\vec{d_1}$ and $\vec{d_2}$, as shown in Fig. 2) respectively, when applying PCA (principal component analysis) algorithm [15] to the image set with distance to the road segment less than δ, and $\vec{d_r}$ is the direction of the road segment.

3.2 Check-ins and scenic view score

Popular roads where users can glimpse more natural view or road-side tourist attractions (e.g., churches, palace, and squares) are also preferred during driving. Thus, to score the scenic view of a road, the POIs on or near the road should be also taken into consideration. Fortunately, compared to the geo-tagged image data which does not have the explicit information about a POI, check-in data not only contains the information about the inherent attributes of a POI (e.g., the longitude, latitude, a hierarchical category description), but also how many times that the POI was checked-in during the past time, which is a good indicator of its popularity. Inspired by the idea that POIs with some specific categories would contribute relatively more on its scenic view [12], we thus intentionally divide the POIs into three groups according to their category labels, as shown in Table 1. The scenic view of a given road segment $e(n_i, n_j)$ using the check-in data can be computed as follows:

$$\mathcal{S}_{checkin}(e(n_i, n_j), \{ck\}) = \sum_{k=1}^{3} w_k \cdot \frac{sizeof(\{ck|dist(ck.v_{id}, e(n_i, n_j)) < \delta \cap catg(ck.v_{id}) \in Group_k\})}{sizeof(\{ck\})}, \tag{3}$$

where $dist(ck.v_{id}, e(n_i, n_j))$ measures the geo-distance from the venue to the road segment, and only the check-ins at venues with the distance to the road segment less than δ are counted, which is similar to the case of geo-tagged image data. Moreover, those check-ins are weighted differently according to the group of the corresponding checked-in venues, roughly followed the idea in Ref. [12], which investigates the scenic view and the surrounding POI categories of a travel route quantitatively. Results suggest that POIs belonging to the *natural scenery* and *tourist attraction* generally contribute more on the scenic view of the travel route than other groups. Therefore, check-ins at venues belonging to Group 1 (i.e., natural scenery) are weighted higher than the other two groups in this paper. Specifically, we empirically set $w_1 = 0.65, w_2 = 0.3$ and $w_3 = 0.05$.

Table 1 Three groups of POIs

Group name	Category labels
Natural scenery	park, garden, lake, forest, mountain, beach, sea, river, bridge, harbor, scenic, hiking.
Tourist attraction	museum, palace, church, gallery, memorial, monument, square, zoo, university, historic site, square.
Others	restaurant, cafe, hotel, etc.

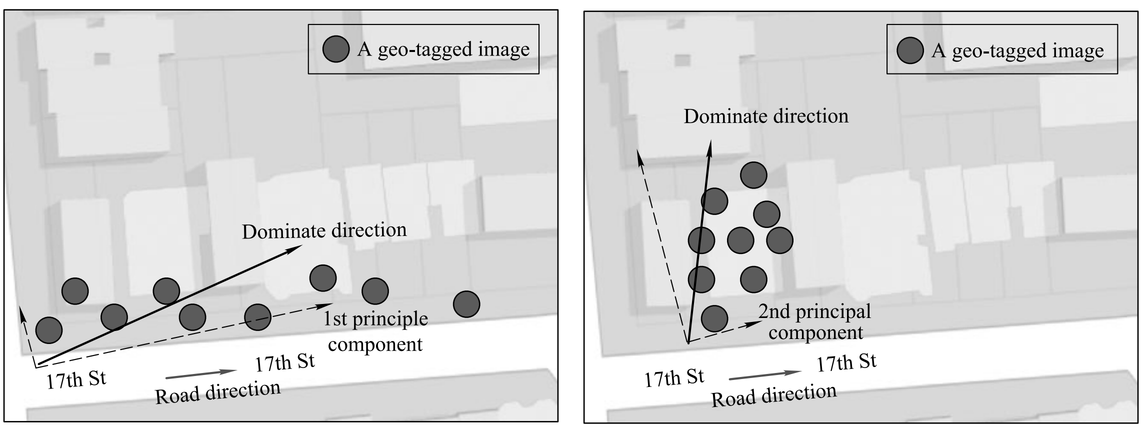


Fig. 2 Illustrative example of two geo-tagged image distributions with the same density but different dominate directions

3.3 Integration of geo-tagged images and check-ins

Given the geo-tagged image data and check-in data, the scenic view score of a road segment is integrated based on Eq. (4).

$$\mathcal{S}(e(n_i, n_j), \{gim\}, \{ck\}) = \mathcal{S}_{image}(e(n_i, n_j), \{gim\}) \times \mathcal{S}_{checkin}(e(n_i, n_j), \{ck\}). \quad (4)$$

Figure 3 shows cumulative distribute function (CDF) result of the scenic view score of all road segments in the road network. We can observe that only 5% of road segments have a value of score bigger than 0.05, and around 85% of road segments even do not have a score.

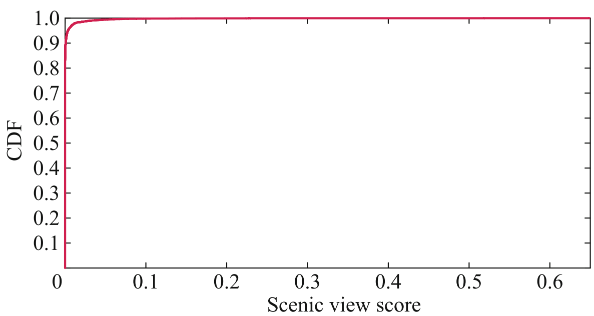


Fig. 3 CDF result of the scenic view score of all road segments

Remark There are many different weighting algorithms to integrate the contributions of geo-tagged images and check-ins on scoring a given road segment, and also different weighting mechanisms would result in different values of score. Furthermore, one kind of data might contribute more than the other one. At the current stage, we are more focused on demonstrating the effectiveness of the introduction of the new kind of user-generated data (i.e., check-ins) on quantifying the score of the scenic view of the road segment. Thus we simply product two kinds of scores in the integration. In the near future, we plan to explore more different weighting algorithms and investigate the related influence on the framework performance.

4 Scenic route planning approach

With the results returned from modelling phase, the objective of scenic route planning is to add the road segments[8] to travel (or visit) to maximize the total scenic view score while satisfying the user-specified constraints (i.e., the starting and ending points, the maximum travel distance). The essence is how to select road segments and determine their ordering. The problem is NP-hard and suffers from combination explosion. On one hand, some road segment has a higher scenic view score but at a higher cost (resulting in a longer travel distance) if included in the travel route. On the other hand, there are many possible orders to travel the selected road segments, and different travelling orders would result in different total travel distances. Furthermore, for most of road segments, they have two driving directions. From a starting point to an ending point and a passing-by road segment, the resulted total travel distance is varied if the road segment is traversed from different driving directions. To maximize the route score without exceeding the allowed maximum travel distance, we propose a three-step procedure, detailed as follows.

• Step 1 Interested area determination There are thousands of road segments in a road network, some of which are far away and cannot be travelled due to the budget constraint. Thus, to improve the efficiency of route planning, we first determine the interested area according to locations of the given starting and ending points. The minimal rectangle area which covers starting and ending points is selected as the interested area. Only road segments lying in the area are qualified to be the candidates for travelling. One obvious advantage of applying this rule is that the efficiency can be greatly improved. We argue that the simply rule is reasonable since the scenic roads outside the area can be hardly selected due to the constraint of maximum travel distance imposed by the user.

• Step 2 Driving direction determination For a given road segment, its driving direction is determined by comparing the value of $shortestDist(p_o, n_i) + shortestDist(n_j, p_d)$ (the distance of the black dashed line in Fig. 4) to the value of $shortestDist(p_o, n_j) + shortestDist(n_i, p_d)$ (the distance of the blue dashed line in Fig. 4), where $shortestDist(a, b)$ gets the shortest distance from point a to point b. We choose the one that can lead to a smaller travel distance. If the two distances are with the same value, the driving direction is determined as the direction from the node closer to the starting point to the other node. As can be observed, the most time-consuming procedure is the shortest path computation given the starting and ending points. Fortunately, the number of scenic road segments in the determined interested area is small and limited. By applying the rule repeatedly, the driving directions of any road segment can be determined once given the locations of starting and ending points. In real situations, for a given road segment, it usually can be traversed in two directions. Suppose a recommended scenic travel route can include N

[8] In the rest of presentation, without special explanation, the road segment refers to the one with scenic view score greater than 0, i.e., the scenic road segment

scenic roads, there would be ($2^N \times N!$) combinations in total. Therefore, it is impossible to immense a response within an acceptable time especially when N is large. To ensure a quick response, in our current study, we simply adopt the proposed rule.

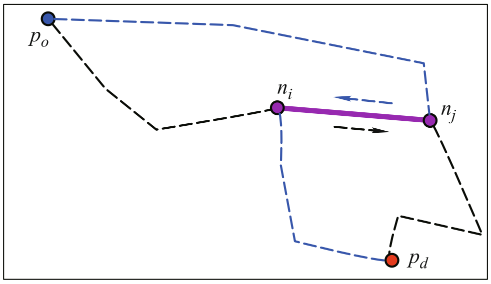


Fig. 4 Demonstration of the rule of driving direction determination

• Step 3 Road segment selecting and ordering As observed in Fig. 3, there are only a few number of scenic road segments in the city, and the number is even smaller in the interested area. An intuitive idea is to select road segment with the highest score in the interested area and add it into the travel route, however, this strategy may use up the travel distance if the highest-score road segment is far away, and forbid adding more new high-scored road segments. We also call the intuitive strategy as the *highest-score-first selecting* (HfS). To make a trade-off between the scenic score of an individual road segment and the number of road segments, we propose a heuristic algorithm called *probability-based selecting* (PbS) strategy based on the idea that the road segment with a higher scenic view score would be selected and added into the route with a higher probability. As a comparison, the strategy which is based on selecting the road segment randomly regardless its scenic view score is also adopted. We call it as the *random-based selecting* (RbS) strategy. HfS and RbS are used as baseline approaches.

Another key issue is the selected road segment ordering. As discussed previously, different road segment orders would result in different travel distances, leaving different margins for adding in more road segments. A straightforward way is to enumerate all the order combinations and pick up the one with the minimal travel distance. The complexity is $O(N!)$, where N is the number of the selected road segments. It is very time-expensive. To simplify the problem, we propose an iterative process consisting of road segment *selecting-adding-ordering*. For instance, based on the proposed selecting strategies, a road segment would be selected and added into the route at the first iteration if the resulted route would not violate any constraint, such as the black dashed line in Fig. 5. At the second iteration, another new road segment would be selected (e.g., $e(n_k, n_l)$ in Fig. 5), and we follow the *shortest distance principle* to determine the order. There are two options that the newly selected road segment $e(n_k, n_l)$ can be added, i.e., before or after the previously added $e(n_i, n_j)$. To be more specific, we assume the scenic travel route is $p_o \rightsquigarrow n_i \rightarrow n_j \rightsquigarrow pd$[9] after the first iteration. In the next iteration, suppose $e(n_k, n_l)$ is selected, the newly shortest path can be determined by comparing the distances between $p_o \rightsquigarrow n_i \rightarrow n_j \rightsquigarrow n_k \rightarrow n_l \rightsquigarrow pd$ and $p_o \rightsquigarrow n_k \rightarrow n_l \rightsquigarrow n_i \rightarrow n_j \rightsquigarrow pd$. The distance comparison can be quite efficient due to the following two aspects: 1) the pair-wised shortest paths and distances between the scenic road segments can be computed and stored a priori, moreover, the number of scenic road segments is small and limited, as shown in Fig. 3; 2) the number of computation of the shortest paths and distances from the starting point to each scenic road segment and from itself to the ending point is also limited. Finally, we just choose the one that can lead to a shorter travel distance as a shorter travel distance may allow to add more road segments, probably implying a better travel route. As can be expected, there are $(n-1)$ options that the newly selected road segment can be added if the travel route has already added n road segments in. Thus, the complexity is reduced to $O(N^2)$.

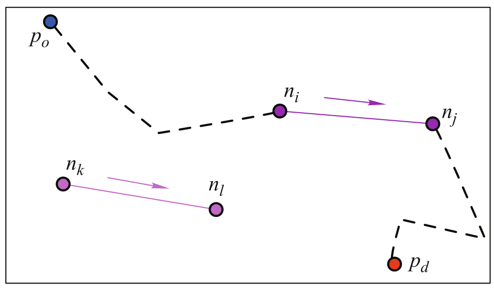


Fig. 5 Demonstration of road segment selecting-adding-ordering process (arrows above the road segments refer to the driving directions)

Algorithm 1 summarizes the whole procedure of the scenic travel route planning. Lines 1–4 refer to the initialization. Based on the user travel route query, the interested area and the driving direction of the road segments in the area will be first determined. We also rank the road segments according to their scenic view scores (line 2). The travel route is initialized as the shortest path from p_o to p_d (line 4). Lines 5–9 illustrate the iterative process of road segment selecting, adding and ordering. At one iteration, a new road segment will be selected based on our proposed strategies, and then added in the current travel route (line 6), Meanwhile, the se-

[9] $p_i \rightsquigarrow p_j$ denotes the detailed shortest path from p_i to p_j

lected road segment will be removed from the set of road segments to avoid being selected again. The iteration will be terminated once no more new road segments can be added or the number of iterations is equal to the user-specified maximum value (line 5). Note that, for the PbS and RbS selecting strategies, the algorithm should be run repeatedly to ensure a high-quality travel route. Each run is independent and can be easily implemented in a parallel way. Thus, the total computation time needed is equal to the one corresponding to the most time-expensive run. We compare the computation time cost for three different approaches in the evaluation part.

Algorithm 1 Scenic travel route planning

Input: A travel route query $TRQ = (p_o, p_d, dist_{\max})$;
Scenic road network G_s.
Output: A travel route (TR)
1: $G'_s = IAD(G_s, p_o, p_d)$ //The determination of the interested area.
2: Rank the road segments in G'_s according to the scenic view score.
3: $maxIter = m$; $curIter = 0$
4: $TR = shortestPath(p_o, p_d)$
5: **while** $(dist(TR) < dist_{\max})||(curIter < maxIter)$ **do**
6: $TR \leftarrow TR + e_{selected}$ //$e_{selected}$ is the road segment selected based on our strategies.
7: $\{e\} = \{e\} - e_{selected}$ //The selected road segment will be removed.
8: $curIter = curIter + 1$
9: **end while**

5 Experimental evaluation

In this section, we first describe the experimental setup, then present the evaluation results on the efficiency and effectiveness of our proposed ScenicPlanner framework.

5.1 Experimental setup

• Data preparation Three data sets in the Bay Area in the city of San Francisco are used, i.e., the road network, the geo-tagged image data, and the check-in data. Statistical information about the three data sets is shown in Table 2.

Table 2 Statistics of the three data sets

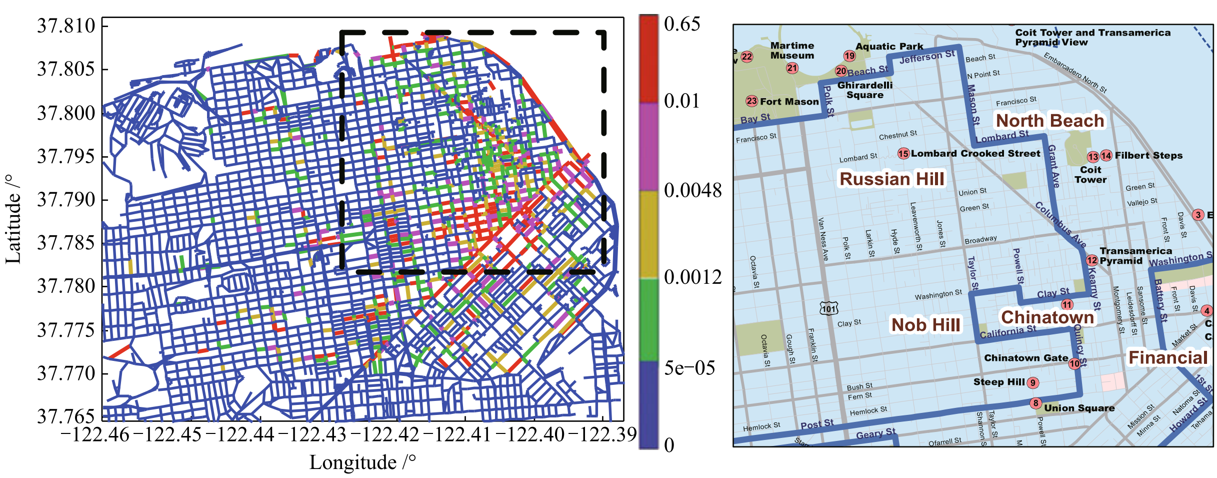
Datasets	Properties	Statistics
Geo-tagged image data	# of images	31 022
	# of users	1 571
Check-in data	# of check-ins	110 214
	# of users	15 680
Road network	# of nodes	3 771
	# of road segments	5 940

• Evaluation environment All the evaluations in the paper are run in Matlab on an Intel Core i5-4460 PC with 4-GB RAM and running Windows 7 operation system.

5.2 Evaluation on scenic road network modelling

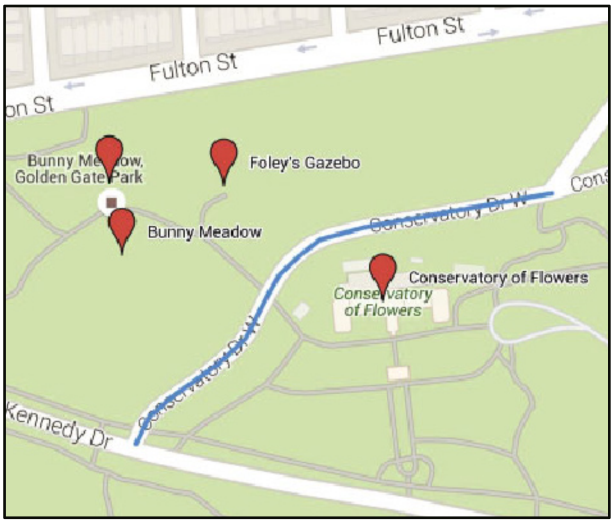
The scenic road network modelled by leveraging two user-generated digital footprints is shown in Fig. 6(a). For comparison, we also provide a part of “49-Mile Scenic Drive” for the selected rectangle region in the road network in Fig. 6(b). From the results, we can see most of road segments in the urban area are scored extremely low. Moreover, the road segments which are scored higher are generally consistent with the designated scenic road tour recommended by the local government, demonstrating the effectiveness of our proposed scenic road network modelling approach.

We also compare our scenic road network modelling approach to the previous work which is solely based on geo-tagged image data. The premise of the modelling approach in Ref. [16] is: the roadway is a scenic one if along which a large number of photos are densely distributed. Nevertheless, it fails to take category information about POIs into

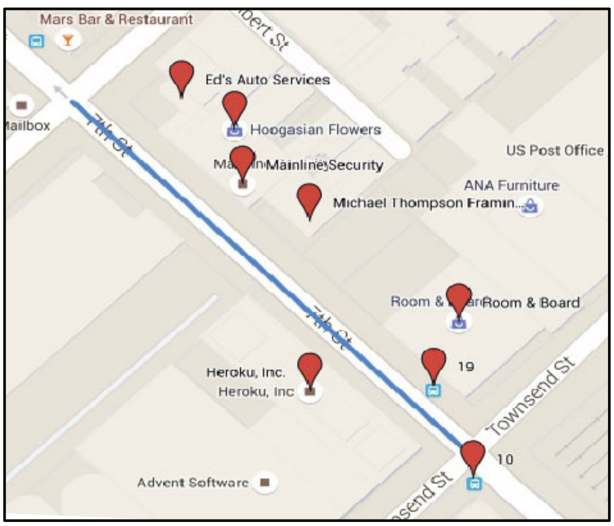


(a) (b)

Fig. 6 Result of (a) scenic road network modelling and (b) a part of the 49-Mile Scenic Drive consideration which is rooted by the fact that geo-tagged image data does not contain such information explicitly. Taking the two road segments shown in Fig. 7 as an example, the road in Fig. 7(a) is the “Bicycle Route 65”, which is a famous driving road due to its attractive scenic view. As can be seen, though the “Bicycle Route 65” is surrounded by only four POIs (i.e., “Conservatory Flows”, “Gold Gate Park” and so on), it also offers a pleasant driving experience. The road in Fig. 7(b) is the “7th St”, which is a regular and normal commercial urban street. It is surrounded by at least eight popular POIs (twice more than that in “Bicycle Route 65”), but they are more preferred for shoppers. Hence, the road in Fig. 7(a) should be scored higher. The “Bicycle Route 65” is ranked 23rd by our modelling approach but ranked 234th by approach in [16]; “7th St” ranked 1 004th by our modelling approach but ranked 12th by approach in [16]. In summary, our modelling approach achieves a more reasonable result as we extract the complementary information provided by two data sources.



(a)



(b)

Fig. 7 Two road segments. (a) Bicycle Route 65: a famous driving road due to its attractive scenic view; (b) 7th St: a regular commercial urban street

5.3 Evaluation on scenic route planning approach

We evaluate three different route planning approaches (i.e., HfS, PbS and RbS), and present the comparison results on the scenic score of the travel route and the computation time respectively. We also provide some additional attributes along the planned routes resulted by different approaches, including the total number of images, the number of different groups of POIs and respected check-ins. In particular, we select five origin-destination (OD) pairs for the evaluation. Table 3 shows the starting and ending locations of the selected five OD pairs.

Table 3 Starting and ending locations of the selected five OD pairs

OD pair	Start	End
1	New Strangers Home Baptist Church	Russian Hill Park
2	Lombard Gate	Museum of Vision
3	Tenth & Harrison Car Wash	Music Intelligence Solutions
4	Safeway	Marina Yacht Harbor
5	Union Square	Ghirardelli Chocolate

Figure 8 shows the results of the scenic score of the planned travel routes for the selected OD pairs. For all five OD pairs, as can be seen, PbS approach achieves the highest scenic score, while RbS approach gets the lowest one. The scenic score obtained by HfS is in-between, better than that of RbS, worse than that of PbS. What is more, among all five OD pairs, for all of three approaches, three of them are with quite small value of scenic score. This is probably caused by: both starting and ending points of the three OD pairs locate in the downtown area, in which the surrounding POIs on road segments are dominated by ones belonging to Group 2 and Group 3 (refer to Table 1).

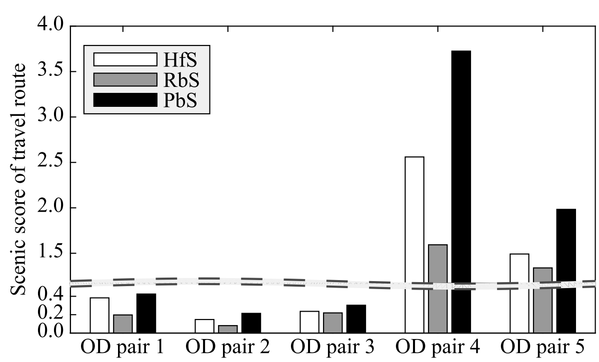


Fig. 8 The scenic score of the travel routes resulted by different route planning approaches

We also show the results of computation time cost of three approaches for the selected OD pairs in Fig. 9. For all five OD pairs, PbS approach needs the most of computation time, HfS costs the smallest amount of computation time. The computation time cost is less than half a minute, which can be acceptable for most of users. As discussed earlier in Section 4, PbS selects the road segment with a higher scenic score and with a higher probability, thus additional probability computation is required, leading to an increase of the computation time, compared to HfS and RbS. We can also observe that the computation time cost of all three approaches for OD pair 1 is much greater than the other four OD pairs, which is due to the fact that the interested area of OD pair 1 is with much denser road network (a bigger number of nodes and edges) and thus more iterations are required to obtain a good-quality travel route.

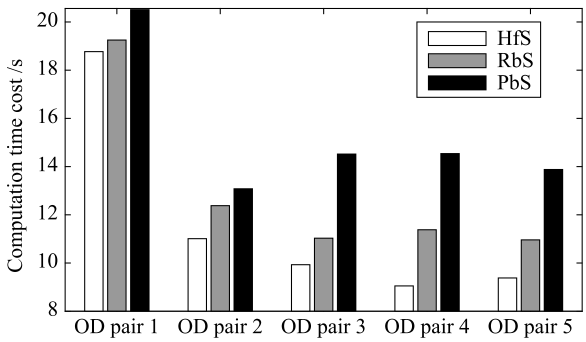


Fig. 9 Computation time cost of different route planning approaches

To better understand how three approaches differ in the planned travel routes, we further provide the statistical information about the number of images, the number of POIs/check-ins distribution on each group, and the number of scenic road segments included in the travel routes obtained by different approaches for all selected five OD groups, as shown in Table 4. We observe that PbS approach achieves either the biggest number of images or the biggest number of POIs and check-ins belonging to Group 1 (i.e., natural scenery), demonstrating the capability of the proposed PbS approach in finding the near-optimal travel route. We can also observe that the number of images associated with the travel routes obtained by RbS is the smallest. With the travel routes obtained by PbS approach, users can visit the biggest number of scenic road segments in four out of five selected OD pairs.

To demonstrate the effectiveness of the proposed framework on the planned travel routes as well as their differences, we plot three travel routes obtained by three approaches (i.e., Hfs, RbS, PbS) for a selected OD pair on the Google map respectively, as shown in Fig. 10. We manually select some

Table 4 Statistics of the number of images and POIs/check-ins distribution on each group of travel routes obtained by different approaches

OD pair	Approaches	# Images	# POIs (# Check-ins)			# of scenic roads
			Group 1	Group 2	Group 3	
1	HfS	1737	5(16)	5(34)	170(1849)	23
	RbS	309	**6(15)**	2(29)	59(367)	7
	PbS	**1970**	2(11)	4(32)	182(1930)	**31**
2	HfS	1064	1(3)	1(2)	79(753)	14
	RbS	177	**4(20)**	3(7)	37(246)	9
	PbS	**1090**	2(3)	3(8)	109(971)	**19**
3	HfS	**879**	7(10)	0(0)	81(837)	15
	RbS	766	8(55)	0(0)	168(1604)	**23**
	PbS	787	**10(89)**	3(7)	162(1482)	21
4	HfS	1446	**66(955)**	1(9)	385(3956)	66
	RbS	1256	29(128)	1(9)	361(3913)	55
	PbS	**2375**	59(806)	1(9)	459(5089)	**73**
5	HfS	1510	16(54)	0(0)	225(2241)	34
	RbS	1200	13(52)	0(0)	195(2127)	37
	PbS	**1564**	**27(69)**	1(9)	267(3266)	**46**

representative POIs (marked as stars) on each travel route, which are either with frequent check-ins or surrounded by a big number of images. Note that the number of stars on the travel route is related to its scenic score. The bigger number of stars implies the corresponding scenic score is also higher. For the travel route obtained by RbS (i.e., the black solid line in Fig. 10), we can see that the number of stars is the smallest, moreover, it also has the fewest common POIs with the other two travel routes (i.e., three gray stars and two cyan stars). With the HfS approach, the system first recommends users to make a dedicated detour to visit some distant scenic roads (the bottom part of blue solid line in Fig. 10), since the approach favors visiting high-score scenic roads no matter how far away. We also observe that the travel route obtained by HfS include much more common POIs with the one obtained by PbS (i.e. nine green stars), compared to the one obtained by RbS. For the travel route obtained by PbS approach (i.e., the red solid line in Fig. 10), it has the largest number of stars. We can also see that the route is more smooth (i.e., with less zigzag parts) than the other two routes, suggesting the effectiveness of our system.

We also design an experiment study to show how far the solutions obtained by the heuristic algorithm are from the ones obtained by the optimized methods as well as the ideally optimal ones. Specifically, we compare their results w.r.t scores and computation time costs, as shown in Table 5. Note that the dynamic programming [17] is adopt as the optimized method, and the ideally optimal travel route is obtained by the simple enumeration process. In terms of the route score, PbS can get a high-quality travel route, with the value quite close to the one obtained by the dynamic programming. In

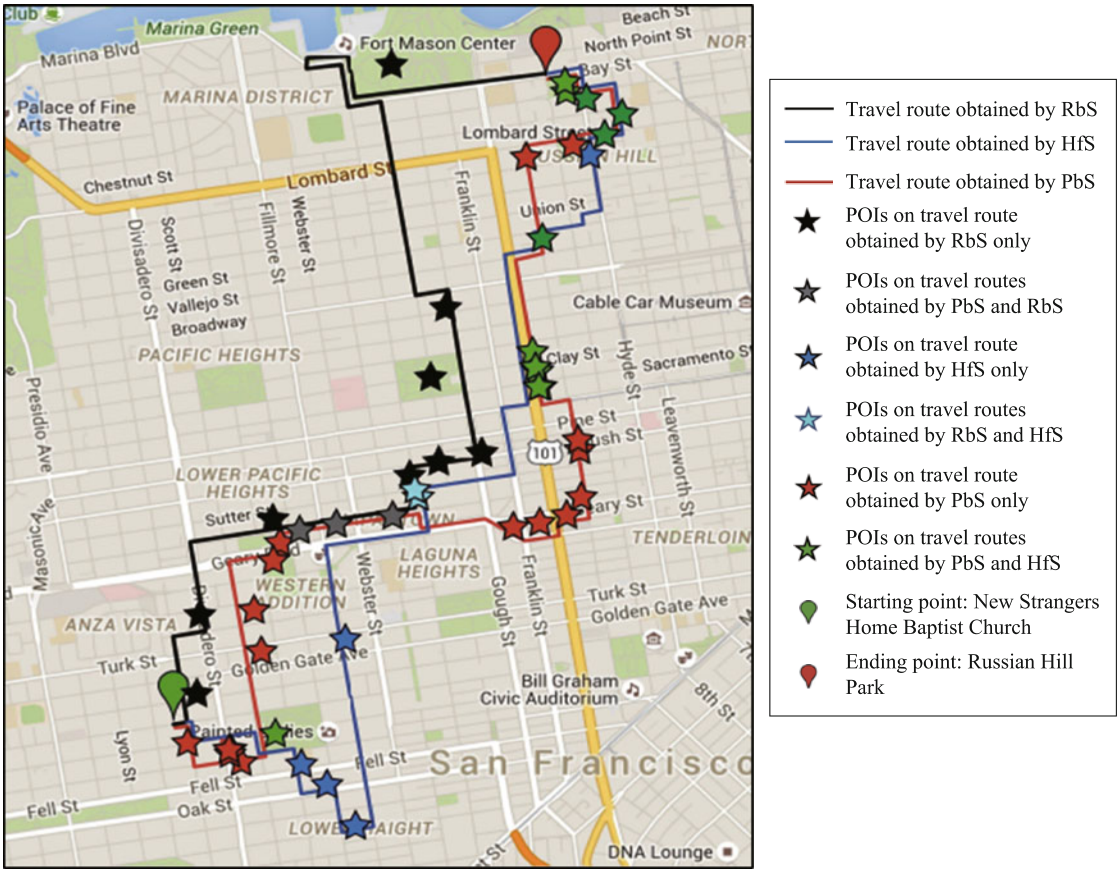


Fig. 10 Comparison results of three planned travel routes obtained by three approaches

terms of the computation time, PbS is the most efficient, while enumeration needs more than three hours. Considering the fact that it is really time-consuming to get the optimal travel route through an enumeration process, the distance of the OD pair is set to small (i.e., 1.41km), as a result, there are seven scenic roads inside the interested area.

Table 5 Comparison results of different approaches

Approaches	Route score	Computation time/s
PbS	0.005 5	5.12
Dynamic programming	0.005 6	83.76
Enumeration	0.008 2	1.13×10^4

6 Related work

6.1 Geo-tagged and check-in data mining

Geo-tagged image and check-in data have been mined to support various applications, having attracted lots of attentions from researchers during recent years. To name a few, how to efficiently manage them has become a critical issue as geo-tagged image data is accumulating rapidly, thus Ref. [18] provided a framework to automatically select a summary set of photos for better accessible. Geo-tagged images taken by different users at different locations may concern the same landmark, thus many studies on identifying and classifying landmarks through data mining algorithms have been done [19, 20]. The geo-tagged image data is a result of crowds who share their photos on social media sites behind which is the wisdom of the crowd [21], hence knowledge and patterns of our human society have been discovered, such as (personalized) landmark recommendation, frequent associated POI sequences suggesting, the heat-map of landmark popularity at different time understanding [8, 10, 19, 22–25]. Similarity, knowledge hidden in check-in data has been mined to support similar applications [1, 9, 26, 27]. However, the major difference between geo-tagged image and check-in data is that the latter one contains rich and explicit information about the POIs. To the best of authors' knowledge, there is not any previous work on exploring the complementary information contained by two user-generated digital footprints in the field of travel route planning.

6.2 Travel route planning

There has been quite some work on planing travel route from one point to another point with non-stop in a city. Systems with objective of the shortest distance (or time) are the most common ones, and many commercial navigators and online map services have provided such travel routes. Considering that the traffic condition is highly dynamic at different time of the day or under different weather, the time-dependent shortest time travel route is also one of the common objectives [28, 29]. There is also some work on planning the shortest travel route integrating the real-time traffic information, such as avoiding roads with high congestion [30]. New objectives that go beyond the shortest distance (time) have been recently appeared in the literature. To number a few, Sharker et al. [31] considered the recommendation of healthy routes (i.e., maximizing the physical activity) to pedestrians. Quercia et al. [32] suggested "happy", "pleasant" travel routes by foot to travellers. Kim et al. [33] made use of the sentiment of geo-tagged image data to recommend routes that are friendlier, more enjoyable and potentially safer. Similarly, based on crime data, Galbrun et al. [34] selected travel routes based on multiple criteria, such as the distance and the safe. Additionally, some constraints are often emphasized, such as bypassing some given POIs (with some specific attributes), and the maximum travel time. Closer to our work, Zheng et al. [16] presented a *GPSViewer* system, with the objective of planning a driving route with scenery and sightseeing qualities, making use of geo-tagged image data to incorporate the scenic factor into the routing. The weight of edges in the road network is a weighted summary of the travel distance and scenic view that can be negative, although the shortest pathfinding algorithm adopted in [16] can work in network with negative weights, it may suffer from the problem of negative loops (all weights in the loop are negative), failing to provide a satisfactory travel route to users. Moreover, based on the method proposed in [16], users cannot get a travel route with a controllable driving distance. On the top of the GPSView system, our ScenicPlanner system improves in the following two main aspects: 1) we model the scenic road network in a more reasonable and accurate way, by leveraging the complementary information provided by Flickr geo-tagged image data and Foursquare check-in data; 2) we use the total travel distance as the constraint which can be customized, and ScenicPlanner works to suggest the travel route with the highest scenic score under the given constraints to users.

7 Conclusion and future work

In this paper, we present a novel framework called ScenicPlanner to recommend the travel route with the best scenic view to users given the constraints of starting, ending points and the maximum travel distance. The framework contains two major modulars, i.e., scenic road network modelling and scenic route planning. More specifically, we first enrich the road network and assign a proper score to each road segment by extracting relevant information from geo-tagged image and check-in data sets. Then we propose heuristic algorithms for scenic route planning with a novel and comprehensive process that consists of interested area determination, road segment driving direction determination and road segment selecting and ordering. Using real-world data sets which include the road network data crawled from OSM platform, a large-scale geo-tagged image data generated by 1 571 Flickr users in a year and check-in data left by 15 680 Foursquare users in six months in the Bay Area in city of San Francisco, USA, we demonstrated the effectiveness and efficiency of our proposed framework.

In the future, we plan to broaden and deepen this work in several directions. First, we plan to develop more advanced route planning algorithms to get better quality travel routes (or solutions for the problem) such as adopting some index and efficient algorithms to speed up the computation of the point-wised distance in a road network and evolution algorithms, and evaluate the theoretical gap between the resulted solution and the truly optimal one. Second, we plan to model the scenic road network at different time of the day and different seasons of the year and integrate the user travelling preferences, on the basis of which we are able to suggest the personalized best travel routes at different time. Moreover, we also intend to mine the GPS trajectory data (e.g., taxi GPS trajectory data) to determine the driving direction for the road segments given locations of source and destination. The rationale behind is: for a given road segment, we are able to obtain its frequent bypassing direction from the source to the destination by mining the history GPS trajectory data, which can be used as its driving direction for that given source-destination pair. Finally, we would like to deploy our system on mobile devices, and recruit some volunteers to test our system in actual settings, collecting feedback on how to further improve the service.

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